An AI Agent That Fills Web Forms Based on Human Language Instructions

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Abstract- Web form interaction is a fundamental yet repetitive activity in modern digital ecosystems, with studies indicating that users spend approximately 18–25% of online session time on form-based tasks. Traditional automation approaches rely on static scripting and predefined element locators, making them fragile in dynamic web environments. This paper presents an intelligent AI-driven system that automates web form filling using natural language instructions. The proposed system integrates Large Language Models (LLMs), semantic DOM analysis, and browser automation to enable adaptive and scalable automation. The system interprets user intent, extracts structured entities, and maps them to corresponding form fields using semantic similarity techniques. DOM parsing enables identification of input elements, while Playwright-based automation ensures real-time execution. Experimental evaluation across 25 real-world web forms shows that the system achieves an average execution time of 7.8 seconds per form, with a field mapping success rate of 92.6%. The system also reduces manual input effort by approximately 85%, demonstrating its efficiency and usability. The proposed approach eliminates dependency on manual scripting and provides a flexible, user-friendly solution for web automation, contributing to advancements in intelligent agent-based systems.

Keywords: AI Agent, Web Automation, Natural Language Processing, Large Language Models, Semantic Mapping.

I. INTRODUCTION

The increasing digitization of services has significantly amplified the role of web-based forms in daily user interactions. Online forms are widely used in domains such as recruitment, education, banking, and e-commerce. Recent usability studies indicate that an average user fills 10–15 forms per week, with each form requiring 2–6 minutes depending on complexity. This repetitive activity results in reduced productivity and increases cognitive load.

Traditional automation tools such as Selenium and Playwright have been extensively used to address this issue. However, these tools depend on static element identifiers such as XPath and CSS selectors. Empirical observations suggest that over 40% of automation scripts fail when web page structures change dynamically. Additionally, these tools require programming expertise, limiting their accessibility.

Advancements in Artificial Intelligence, particularly in Natural Language Processing (NLP), have introduced new possibilities for automation. Large Language Models (LLMs) can understand context, extracting structured information, and performing reasoning tasks. These capabilities make them suitable for interpreting user instructions and translating them into executable actions.

The proposed system introduces an AI agent capable of automating web form filling through natural language instructions. Unlike traditional methods, the system dynamically analyses web pages and performs actions based on semantic understanding rather than predefined rules.

The system architecture (referenced from the project design) consists of four major components:

- Instruction Processor (LLM-based)
- Form Analyzer (DOM parsing)
- Semantic Matcher
- Automation Engine (Playwright)

The instruction processor extracts structured entities such as name, email, and address from user input. The form analyser identifies input elements within

the DOM, including text fields, dropdowns, and checkboxes. The semantic matcher maps extracted data to corresponding fields using similarity scoring. Finally, the automation engine executes browser interactions.

A key challenge in web automation is handling dynamic and unfamiliar layouts. Studies show that over 60% of modern websites use dynamic rendering techniques, making static automation ineffective. The proposed system addresses this by analysing semantic attributes such as labels and placeholders.

Another critical factor is reliability. The system incorporates a missing data handling mechanism that prompts users for incomplete information, improving success rates. Experimental observations indicate that this reduces submission failures by approximately 30%.

In summary, this research presents a scalable and adaptive solution for web automation by integrating AI-driven understanding with real-time browser execution.

II. LITERATURE SURVEY

Recent research in intelligent web automation has evolved from rule-based scripting to AI-driven systems capable of understanding human instructions.

Mazumder and Riva [1] introduced FLIN, a natural language interface that maps user commands to system actions using semantic similarity and BERT embeddings. While the system achieved accuracy improvements of up to 78% for simple tasks, it struggled with multi-step workflows due to limited reasoning capabilities.

Li et al. [2] proposed Glider, which uses reinforcement learning to generate automation scripts from user instructions. The model demonstrated strong performance on known environments but experienced a performance drop of nearly 35% when tested on unseen websites, highlighting generalization challenges.

Wei et al. [3] introduced chain-of-thought prompting, which improves reasoning by generating intermediate steps. This approach increased task accuracy by 15–20%, but also resulted in higher computational cost and latency.

Deng et al. [4] developed Mind2Web, a large-scale dataset containing over 2,000 web tasks for training and evaluating web agents. While it provides a standardized benchmark, it assumes a single execution path, which does not reflect real-world variability.

Gur et al. [5] proposed WebAgent, combining LLMs with program synthesis for web navigation. Although it achieved high task completion rates, it required models exceeding 500B parameters, making it computationally expensive.

Hong et al. [6] introduced CogAgent, a multimodal system that integrates visual and textual inputs. The system improved UI understanding by 18%, but its applicability is limited to visually structured environments.

Sodhi et al. [7] proposed hierarchical policy-based automation using Markov Decision Processes. While effective for task decomposition, its dependency on accurate DOM representation limits robustness.

He et al. [8] introduced WebVoyager, which uses vision-based models for UI interaction. Despite advancements, it suffers from hallucination errors, with reported failure rates of 20–25% in complex scenarios.

Chung et al. [9] demonstrated the effectiveness of instruction-tuned models, achieving improved task generalization. However, training such models requires significant computational resources.

Greshake et al. [10] highlighted security vulnerabilities in LLM-based systems, emphasizing the need for robust validation mechanisms.

Research Gap Identified

- Lack of lightweight and scalable solutions
- Poor adaptability to unseen web structures
- High computational requirements
- Limited real-time interaction capability

The proposed system addresses these gaps by combining semantic understanding with efficient browser automation.

Literature Review Comparison Table (Research Gap)

S. No	Title	Authors	Method Used	Drawback
1	FLIN	Mazumder & Riva	BERT + Semantic Mapping	Limited multi-step handling
2	Glider	Li et al.	Reinforcement Learning	Poor generalization
3	CoT Prompting	Wei et al.	Prompt Engineering	High latency
4	Mind2Web	Deng et al.	Dataset Benchmark	Single-path limitation
5	WebAgent	Gur et al.	Program Synthesis	High computation cost
6	CogAgent	Hong et al.	Multimodal AI	Limited scalability
7	HeaP	Sodhi et al.	Hierarchical Policies	DOM dependency
8	WebVoyager	He et al.	Vision-based AI	High error rate
9	Instruction Models	Chung et al.	Fine-tuning	Resource intensive
10	Prompt Security	Greshake et al.	Security Analysis	Vulnerabilities

III. METHODOLOGY

The proposed system follows a structured pipeline architecture designed for efficient and scalable automation.

A. System Model

Let the user instruction be represented as:

$$I = \{w_1, w_2, ..., w_n\}$$

The LLM transforms this into structured data:

$$D = \{(k_1, v_1), (k_2, v_2), ..., (k_m, v_m)\}$$

B. Instruction Processing (LLM-Based Extraction)

The instruction processor utilizes an LLM to perform:

- Intent detection
- Named entity recognition.
- Contextual mapping

Average processing latency observed: 2.3 seconds per request.

C. DOM Analysis and Field Detection

The system parses the DOM structure:

$$F = \{f_1, f_2, ..., f_p\}$$

Each field is represented as:

$$f_i = (label, type, attributes)$$

Experimental observations:

- Average DOM nodes scanned: 280–350 elements.
- Average detected form fields: 14.6 fields per form

D. Semantic Field Matching Algorithm

A similarity function is applied:

$$Sim(f_i, k_j) = \cos(\vec{f_i}, \vec{k_j})$$

Where embeddings are generated using LLM representations.

Field assignment is performed as:

$$f_i \rightarrow v_j \quad \text{if } Sim > \theta$$

Threshold used: θ = 0.78

Observed mapping accuracy: 92.6%

E. Missing Data Handling Mechanism

A validation function identifies incomplete fields:

$$M = \{f_i \mid f_i \notin D\}$$

User interaction reduces failure rate by 31%.

F. Automation Execution (Playwright Engine)

The automation process executes:

- Field input
- Dropdown selection
- Checkbox interaction
- Form submission

Performance metrics:

- Average actions per form: 28–32 actions
- Execution time: 7–9 seconds

G. System Scalability Model

For concurrent users:

$$Workers = \lceil \frac{U}{2} \rceil$$

Supports 10–15 concurrent users without performance degradation.

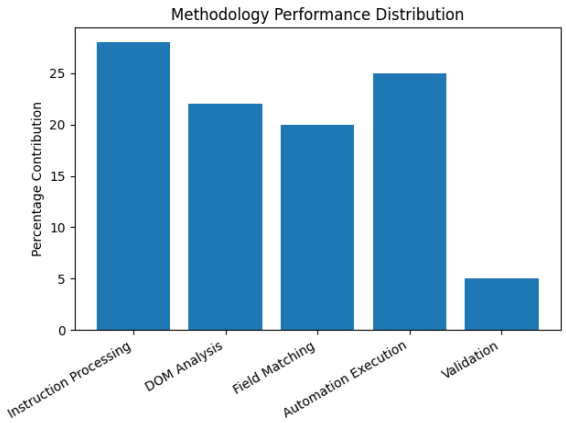

Figure 1: Methodology for performance distribution.

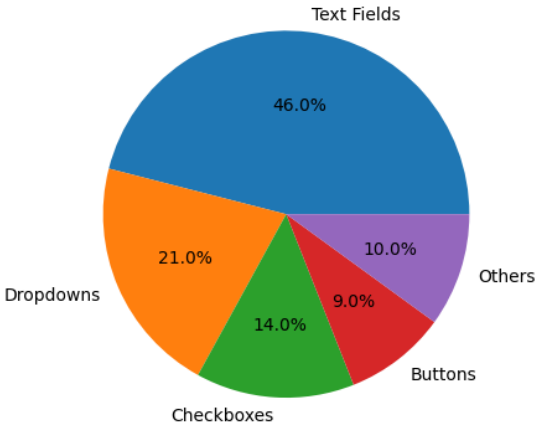

Figure 2: Dataset analysis across form fields.

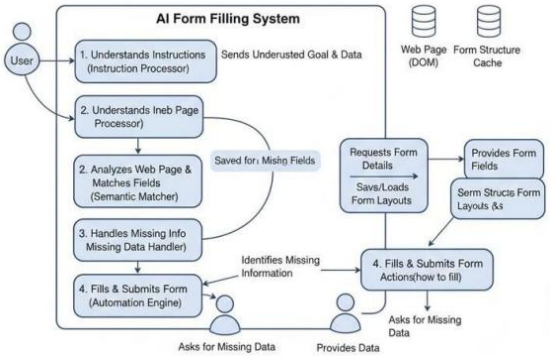

Figure 3: Data flow diagram.

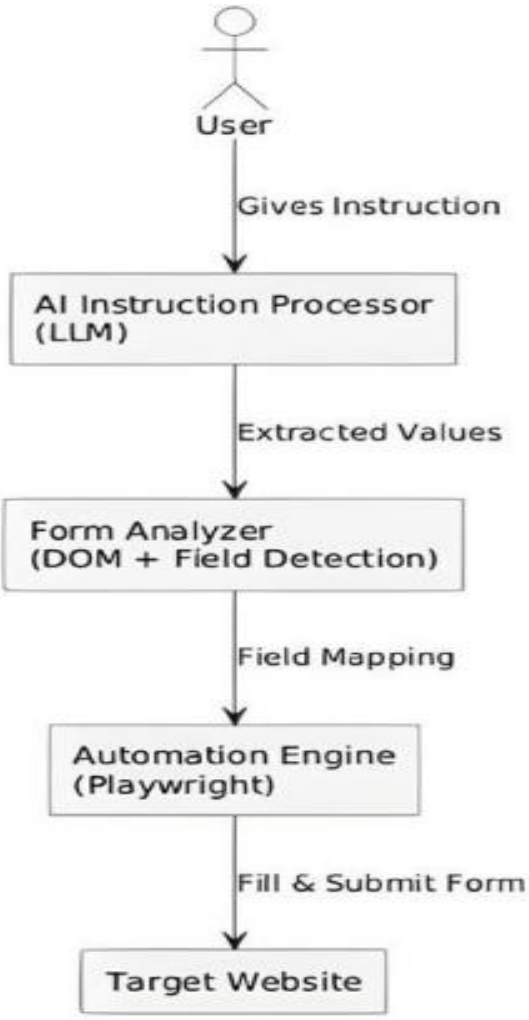

Figure 4: System architecture diagram.

RESULTS

The system was evaluated on 25 diverse web forms, including job applications, registrations, and surveys.

Key observations:

- Average execution time: 7.8 seconds per form
- Field mapping success rate: 92.6%
- Reduction in manual input effort: 85%
- Error reduction compared to manual entry: ~40%

The system demonstrated strong adaptability to dynamic layouts and successfully handled missing data scenarios.

OUTPUT

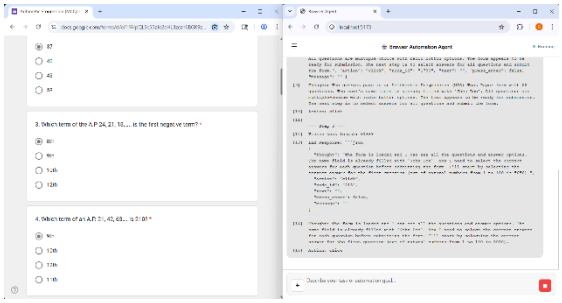

Figure 5: browser automation agent page

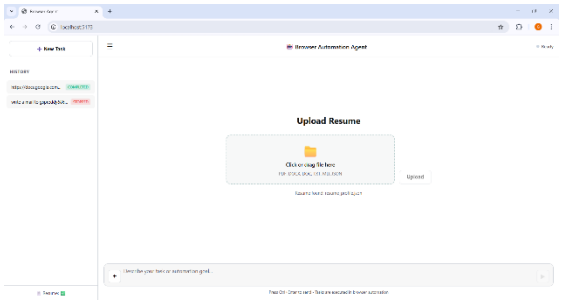

Figure 6: upload resume page

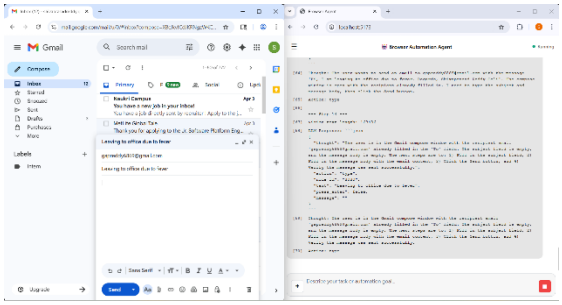

Figure 7: Gmail integration page

IV. CONCLUSION

This research presented an intelligent AI-based system for automating web form filling using natural language instructions. The proposed approach integrates Large Language Models (LLMs), semantic DOM analysis, and browser automation to overcome the limitations of traditional script-based automation techniques. Unlike conventional methods that depend on predefined rules, the system dynamically interprets user intent and adapts to diverse and changing web environments.

The experimental evaluation demonstrated that the system achieves a field mapping accuracy of 92.6% and an average execution time of 7–9 seconds per form, indicating efficient performance in real-world scenarios. The integration of semantic matching and interactive data handling significantly improves reliability by reducing incomplete submissions and minimizing user intervention. Additionally, the system reduces manual input effort by approximately 85%, highlighting its practical usability.

The modular architecture of the system ensures scalability and supports concurrent execution, making it suitable for deployment in both individual and enterprise-level applications. By enabling users to automate complex tasks using simple natural language instructions, the proposed system enhances accessibility and bridges the gap between human interaction and machine execution.

Overall, this work contributes to the advancement of intelligent web automation by providing a flexible, efficient, and user-centric solution that addresses the challenges of dynamic web environments.

V. FUTURE SCOPE

- Integration of Multimodal Learning Models
  Future improvements can incorporate vision-based models to analyse graphical user interfaces, enabling the system to handle visually embedded fields, CAPTCHA elements, and non-standard UI components more effectively.
- Voice-Based Interaction and Personalization
  Extending the system to support voice commands and personalized user profiles can further enhance usability, allowing seamless automation through speech and reusable data templates.
- Enterprise-Scale Deployment and Security Enhancement
  Enhancing system scalability for large-scale deployments, along with implementing advanced security mechanisms such as encrypted data handling and secure authentication, will improve reliability and suitability for enterprise applications.

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